01_eda_pp_vs_oil

December 2, 2025

1 Polypropylene vs Upstream Drivers: Exploratory Data Analysis

Explore whether PP prices co-move with propylene (PGP) and crude; establish sensible baselines before expanding into richer feature sets.

Local files under `data/` are used throughout. Units, currencies, and frequencies may differ, so we normalize and resample to monthly for comparability.

[1]:

```
#pip install -q pandas numpy matplotlib seaborn statsmodels
```

[2]:

```
from pathlib import Path
import sys
import pandas as pd
import matplotlib.pyplot as plt
from IPython.display import Markdown, display

PROJECT_DIR = Path.cwd().parent
DATA_DIR = PROJECT_DIR / "data"
PLOTS_DIR = PROJECT_DIR / "plots"
ARTIFACTS_DIR = PROJECT_DIR / "artifacts"
for folder in (PLOTS_DIR, ARTIFACTS_DIR):
    folder.mkdir(parents=True, exist_ok=True)

sys.path.insert(0, str(PROJECT_DIR / "src"))
from eda_utils import (
    build_audit_table,
    compute_log_returns,
    cross_corr_scan,
    find_candidate_files,
    load_series,
    normalize_base_100,
    plot_beta_scaled_spread,
    plot_leadlag_heatmap,
    plot_normalized_levels,
    plot_rolling_beta,
    plot_scatter_returns,
    rolling_beta_ols,
    rolling_corr,
    to_monthly,
)

plt.rcParams["figure.dpi"] = 150
CLASS_KEYWORDS = {
    "PP": ["pp", "polypropylene"],
    "PGP": ["pgp", "propylene", "c3"],
    "CRUDE": ["brent", "wti", "crude", "oil"],
    "NAPHTHA": ["naphtha"],
}
```

1.1 Discovery & loading

Find candidate files by keyword, load each series with `eda_utils.load_series`, and capture metadata for traceability.

[3]:

```
candidate_map = {
    label: find_candidate_files(DATA_DIR, patterns)
    for label, patterns in CLASS_KEYWORDS.items()
}

loaded_series = {}
discovery_records = []
for label, paths in candidate_map.items():
    if not paths:
        print(
            f"No {label} series found. Expected keywords:␣
 ↪{CLASS_KEYWORDS[label]}"
        )
        continue
    series_list = []
    for path in paths:
        try:
            df = load_series(path, f"{label}|{path.stem}")
        except Exception as exc:
            print(f"Skipping {path.name}: {exc}")
            continue
        series_list.append(df)
        discovery_records.append(
            {
                "class": label,
                "series_name": df.attrs.get("series_name"),
                "file": path.relative_to(PROJECT_DIR),
                "date_column": df.attrs.get("date_column"),
                "value_column": df.attrs.get("value_column"),
                "rows_raw": df.attrs.get("rows_raw"),
                "rows_clean": df.attrs.get("rows_clean"),
                "start": df.attrs.get("start"),
                "end": df.attrs.get("end"),
            }
        )
    if series_list:
        loaded_series[label] = series_list
discovery_df = pd.DataFrame(discovery_records)
if not discovery_df.empty:
    display(discovery_df)
else:
    display(Markdown("**No qualifying series loaded - add data to proceed.**"))
```

```
No NAPHTHA series found. Expected keywords: ['naphtha']
```

```
   class                          series_name   \
0     PP   PP|polypropylene_primary_avg_prices
1     PP               PP|polypropylene_weekly
2     PP         PP|polypropylene_weekly_clean
3    PGP  PGP|polypropylene_primary_avg_prices
4    PGP              PGP|polypropylene_weekly
5    PGP        PGP|polypropylene_weekly_clean
6  CRUDE                 CRUDE|crude_oil_daily
7  CRUDE                CRUDE|crude_oil_weekly
8  CRUDE          CRUDE|crude_oil_weekly_clean

                                               file date_column   \
0  data\prices\polypropylene_primary_avg_prices.csv        Date
1              data\prices\polypropylene_weekly.csv        Date
2        data\prices\polypropylene_weekly_clean.csv        date
3  data\prices\polypropylene_primary_avg_prices.csv        Date
4              data\prices\polypropylene_weekly.csv        Date
5        data\prices\polypropylene_weekly_clean.csv        date
6                   data\prices\crude_oil_daily.csv        Date
7                  data\prices\crude_oil_weekly.csv        Date
8            data\prices\crude_oil_weekly_clean.csv        Date

       value_column  rows_raw  rows_clean      start         end
0  PP_Avg_EUR_per_t        81          81 2018-08-01 2025-04-01
1             Price       520         520 2015-01-04 2025-03-02
2             price       520         520 2015-01-04 2025-03-02
3  PP_Avg_EUR_per_t        81          81 2018-08-01 2025-04-01
4             Price       520         520 2015-01-04 2025-03-02
5             price       520         520 2015-01-04 2025-03-02
6             Close      5426        2712 2015-01-02 2025-10-14
7             Close      1129         564 2015-01-05 2025-10-20
8             Close      1128        1128 2015-01-05 2025-10-20
```

Table note: The discovery summary above lists every file that matched our keyword scan and highlights which date/value columns were inferred so you can quickly spot mislabelled sources.

1.2 Monthly alignment

Resample each raw series to monthly means, keep one preferred series per class, and form wide outer/inner tables.

[4]:

```
monthly_tables = {}
preferred = {}
for label, series_list in loaded_series.items():
    monthly_list = [to_monthly(series) for series in series_list]
    table = pd.concat(monthly_list, axis=1)
    table = table.loc[~table.index.duplicated()].sort_index()
    monthly_tables[label] = table
    preferred_series_name = table.count().sort_values(ascending=False).index[0]
    preferred[label] = table[preferred_series_name]
wide_outer = pd.concat(monthly_tables.values(), axis=1) if monthly_tables else␣
  ↪pd.DataFrame()
monthly_inner = pd.concat(preferred, axis=1).dropna() if preferred else pd.
  ↪DataFrame()
display(Markdown(f"**Monthly outer shape:** {wide_outer.shape}"))
display(Markdown(f"**Monthly inner shape:** {monthly_inner.shape}"))
wide_outer.head()
```

Monthly outer shape: (130, 9)

Monthly inner shape: (123, 3)

[4]:

```
            PP|polypropylene_primary_avg_prices  PP|polypropylene_weekly  \
2015-01-01                                  NaN                  8285.25
2015-02-01                                  NaN                  8748.00
2015-03-01                                  NaN                  8829.40
2015-04-01                                  NaN                  9348.00
2015-05-01                                  NaN                  9142.00

            PP|polypropylene_weekly_clean  \
2015-01-01                        8285.25
2015-02-01                        8748.00
2015-03-01                        8829.40
2015-04-01                        9348.00
2015-05-01                        9142.00

            PGP|polypropylene_primary_avg_prices  PGP|polypropylene_weekly  \
2015-01-01                                   NaN                   8285.25
2015-02-01                                   NaN                   8748.00
2015-03-01                                   NaN                   8829.40
2015-04-01                                   NaN                   9348.00
2015-05-01                                   NaN                   9142.00

            PGP|polypropylene_weekly_clean  CRUDE|crude_oil_daily  \
2015-01-01                         8285.25              47.325500
```

```
2015-02-01                                8748.00           50.724736
2015-03-01                                8829.40           47.854091
2015-04-01                                9348.00           54.628096
2015-05-01                                9142.00           59.372000

            CRUDE|crude_oil_weekly  CRUDE|crude_oil_weekly_clean
2015-01-01                48.224125                     49.246187
2015-02-01                49.986625                     53.093875
2015-03-01                48.135600                     52.875400
2015-04-01                53.463125                     56.592562
2015-05-01                59.418000                     62.724000
```

[5]:
```
audit_input = {label: series for label, series in preferred.items()}
audit_table = build_audit_table(audit_input) if audit_input else pd.DataFrame()
if not audit_table.empty:
    display(audit_table)
    audit_table.to_csv(ARTIFACTS_DIR / "data_audit.csv", index=False)
monthly_inner.to_csv(ARTIFACTS_DIR / "merged_monthly_prices.csv")
```

```
  series first_date  last_date  count  missing_pct  \
0     PP 2015-01-01 2025-03-01    123          0.0
1    PGP 2015-01-01 2025-03-01    123          0.0
2  CRUDE 2015-01-01 2025-10-01    130          0.0

                frequency_note currency  unit source_path
0  monthly (resampled via mean)     None  None        None
1  monthly (resampled via mean)     None  None        None
2  monthly (resampled via mean)     None  None        None
```

Audit note: Use the audit table to confirm coverage (first/last date, missing %), plus currency/unit hints pulled from the raw files.

1.3 Levels (normalized)

Normalize each preferred level series to 100 at the first common observation.

[6]:
```
if not monthly_inner.empty:
    norm_levels = normalize_base_100(monthly_inner)
    fig = plot_normalized_levels(norm_levels, "Normalized Levels (base = 100)")
    display(fig)
    fig.savefig(PLOTS_DIR / "levels_normalized.png", bbox_inches="tight")
    plt.close(fig)
else:
    display(Markdown("*No overlapping monthly series available.*"))
```

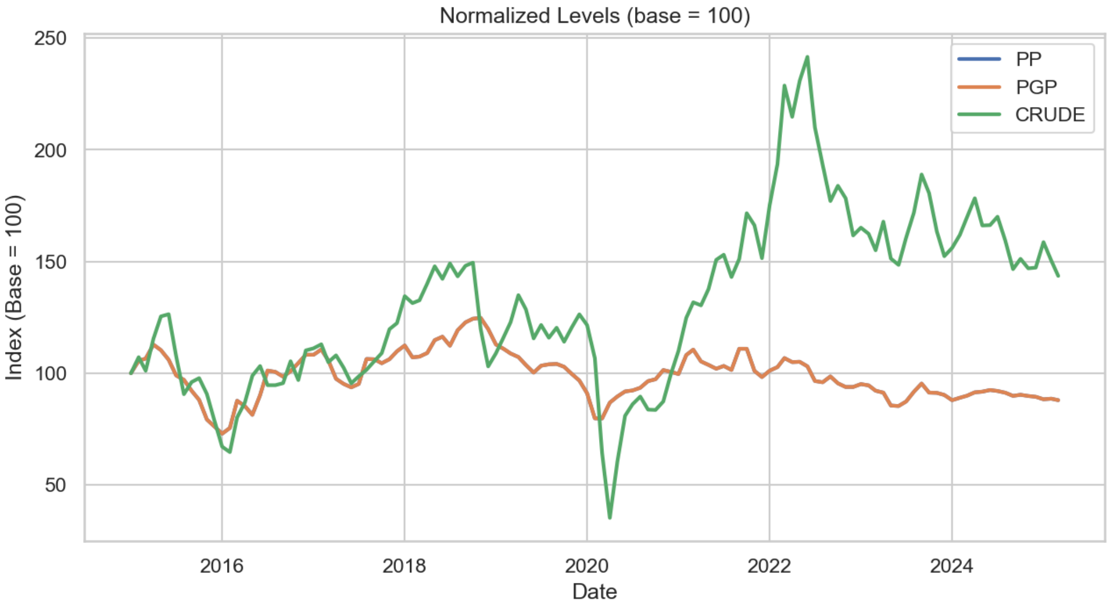


Figure: Normalized level lines let us compare PP and crude trends on a common 100-base scale so different currencies/units do not mask co-movement.

1.4 Returns & correlations

Compute log returns, save clean datasets, and prepare diagnostics for PP vs key drivers.

```
[7]: if not monthly_inner.empty:
         log_returns = compute_log_returns(monthly_inner).dropna()
         log_returns.to_csv(ARTIFACTS_DIR / "merged_monthly_returns.csv")
         display(log_returns.describe().T)
     else:
         log_returns = pd.DataFrame()
         display(Markdown("*Returns unavailable; add overlapping series.*"))
```

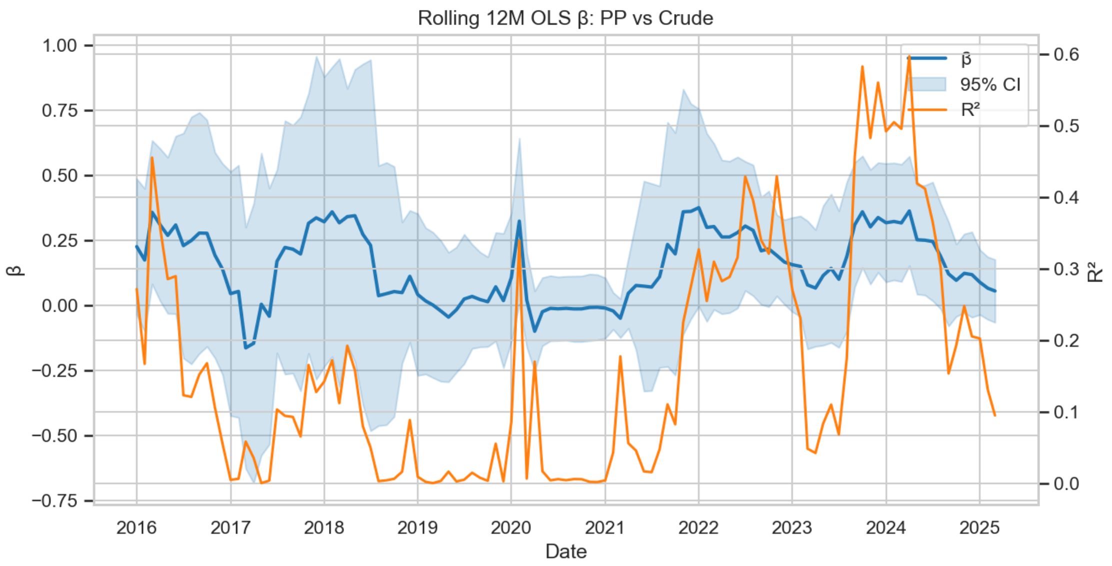
```
       count      mean       std       min       25%       50%       75%  \
PP     122.0 -0.001052  0.042444 -0.131583 -0.023175 -0.001969  0.020649
PGP    122.0 -0.001052  0.042444 -0.131583 -0.023175 -0.001969  0.020649
CRUDE  122.0  0.002964  0.120098 -0.600585 -0.053332  0.019625  0.056092

            max
PP     0.149596
PGP    0.149596
CRUDE  0.535517
```

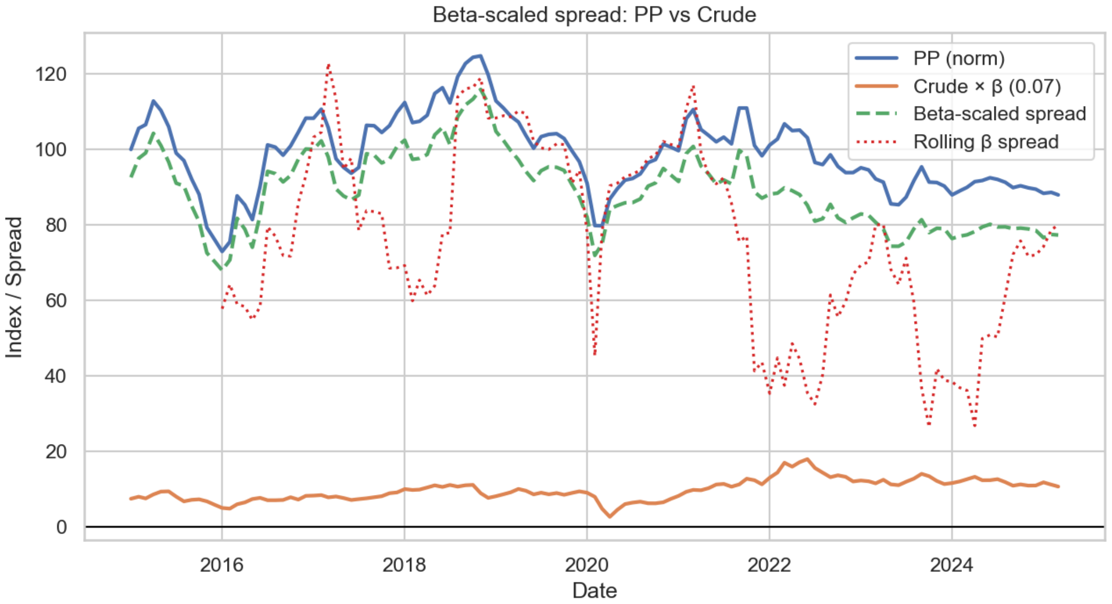
Table detail: The return summary offers mean/volatility/skewness for each monthly log-return series so you can judge distribution shape before modelling.

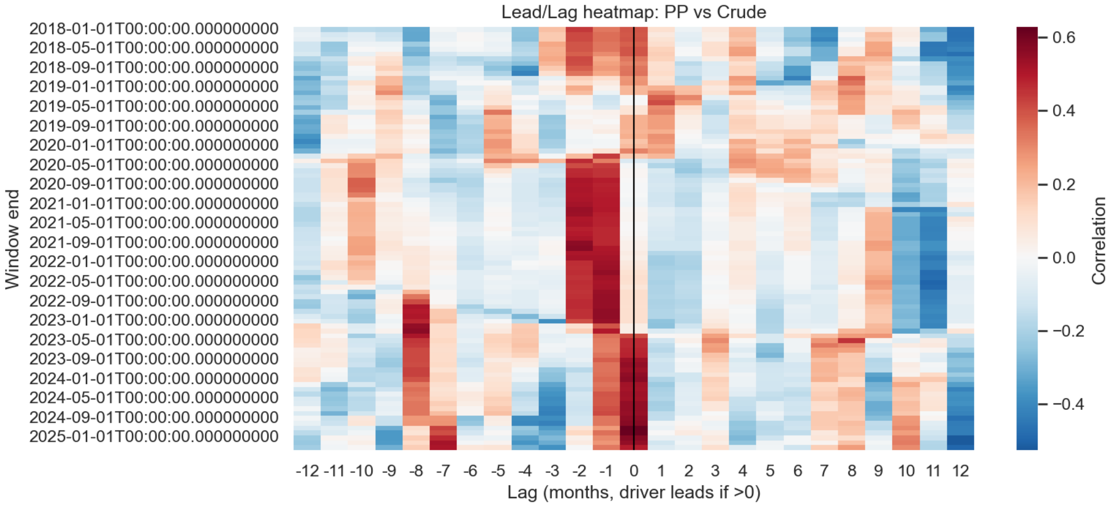
1.5 Headline visuals

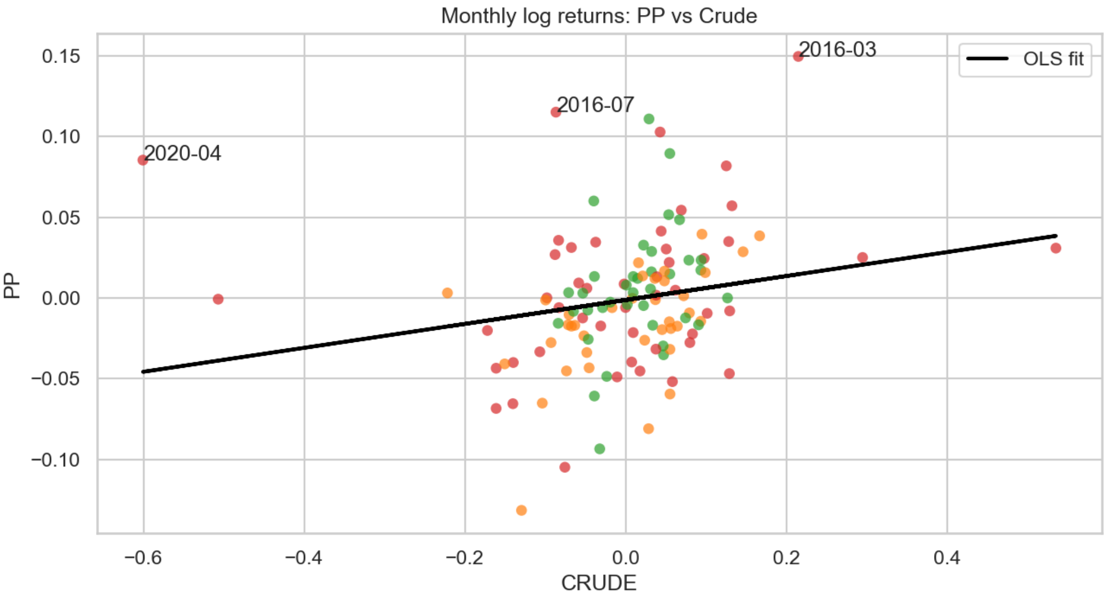
Key diagnostics for PP versus crude oil (or other drivers when available).

[8]:
```
if {"PP", "CRUDE"} <= set(monthly_inner.columns):
    pp = monthly_inner["PP"]
    crude = monthly_inner["CRUDE"]
    pp_ret = log_returns["PP"]
    crude_ret = log_returns["CRUDE"]

    rolling_beta = rolling_beta_ols(pp_ret, crude_ret, window=12)
    if not rolling_beta.empty:
        fig = plot_rolling_beta(rolling_beta, "Rolling 12M OLS  : PP vs Crude")
        display(fig)
        fig.savefig(PLOTS_DIR / "rolling_beta_pp_crude.png",␣
 ↪bbox_inches="tight")
        plt.close(fig)

    beta_series = rolling_beta["beta"] if "beta" in rolling_beta else None
    fig = plot_beta_scaled_spread(pp, crude, beta=None,␣
 ↪rolling_beta=beta_series, title="Beta-scaled spread: PP vs Crude")
    display(fig)
    fig.savefig(PLOTS_DIR / "beta_scaled_spread_pp_crude.png",␣
 ↪bbox_inches="tight")
    plt.close(fig)

    fig = plot_leadlag_heatmap(pp_ret, crude_ret, window=36, max_lag=12,␣
 ↪title="Lead/Lag heatmap: PP vs Crude")
    display(fig)
    fig.savefig(PLOTS_DIR / "leadlag_heatmap_pp_crude.png", bbox_inches="tight")
    plt.close(fig)

    fig = plot_scatter_returns(pp_ret, crude_ret, title="Monthly log returns:␣
 ↪PP vs Crude", label_outliers=3)
    display(fig)
    fig.savefig(PLOTS_DIR / "scatter_returns_pp_crude.png", bbox_inches="tight")
    plt.close(fig)

    rolling_corr_pp_crude = rolling_corr(pp_ret, crude_ret, window=12)
    rolling_corr_pp_crude.to_csv(ARTIFACTS_DIR / "rolling_corr_pp_crude.csv")
    corr_scan = cross_corr_scan(pp_ret, crude_ret, max_lag=12)
    corr_scan.to_csv(ARTIFACTS_DIR / "cross_corr_scan_pp_crude.csv",␣
 ↪index=False)
else:
    display(Markdown("**Add crude data to unlock headline visuals.**"))
```


Rolling 12M OLS β: PP vs Crude
β
95% CI
R²
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
0.6
0.5
0.4
0.3
0.2
0.1
0.0
β
R²
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Date


Beta-scaled spread: PP vs Crude
PP (norm)
Crude × β (0.07)
Beta-scaled spread
Rolling β spread
120
100
80
60
40
20
0
Index / Spread
2016
2018
2020
2022
2024
Date





Figures recap: Rolling tracks relationship strength, the beta-scaled spread highlights sustained divergence, the lead/lag heatmap surfaces timing asymmetry, and the scatter pinpoints outlier months that may warrant narrative follow-up.

1.6 Findings

```
[9]: if not monthly_inner.empty and not log_returns.empty:
         overlap = (
             monthly_inner.index.min().date(),
             monthly_inner.index.max().date(),
        len(monthly_inner),
    )
    corr_pp_crude = None
    if {"PP", "CRUDE"} <= set(log_returns.columns):
        corr_pp_crude = log_returns[["PP", "CRUDE"]].corr().iloc[0, 1]
    bullets = [
        f"- Overlap: {overlap[0]} to {overlap[1]} ({overlap[2]} months).",
        f"- PP vs Crude return correlation: {corr_pp_crude:.2f}." if corr_pp_crude is not None else "- Crude returns unavailable.",
    ]
    if Path(ARTIFACTS_DIR / "cross_corr_scan_pp_crude.csv").exists():
        scan = pd.read_csv(ARTIFACTS_DIR / "cross_corr_scan_pp_crude.csv")
        best = scan.iloc[scan["corr"].abs().idxmax()]
        bullets.append(
            f"- Best lead/lag (PP vs Crude): lag {int(best['lag'])} with corr {best['corr']:.2f}."
        )
    else:
        bullets.append("- Add drivers (PGP/crude) to compute lead/lag diagnostics.")
    display(Markdown("\n".join(bullets)))
else:
    display(Markdown("**Not enough data for findings yet.**"))
```

- Overlap: 2015-01-01 to 2025-03-01 (123 months).
- PP vs Crude return correlation: 0.21.
- Best lead/lag (PP vs Crude): lag -1 with corr 0.36.